

Improved bidirectional long short term memory-based QRS complex detection using autoencoder

Asep Insani¹, Suryo Adhi Wibowo^{2,3}

¹National Research and Innovation Agency (BRIN), Jakarta, Indonesia

²AI Center, Telkom University, Bandung, Indonesia

³School of Electrical Engineering, Telkom University, Bandung, Indonesia

Article Info

Article history:

Received Jun 20, 2023

Revised Dec 7, 2023

Accepted Feb 12, 2024

Keywords:

Bidirectional long short term memory

Deep learning

Electrocardiogram signal

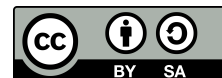
QRS complex detection

Stacked autoencoder

ABSTRACT

In this paper, we propose a new technique to improve QRS complex detection. This technique consists of incorporating an autoencoder and bidirectional long short term memory (BiLSTM). The autoencoder used is a stacked autoencoder and functions as signal filtering. Meanwhile, BiLSTM is used as a detector. Exploration of the effect of hyperparameter in the autoencoder was also carried out to determine the effect on QRS complex detection. Furthermore, the dataset used in this study is the MIT-BIH arrhythmia database. Based on the experimental results, the hyperparameter in the autoencoder that gives a better effect on QRS complex detection is 16-8. Finally, the proposed method out-of-perform state of the art algorithm with accuracy 99.94%.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Suryo Adhi Wibowo

AI Center, Telkom University

Bandung, Indonesia

Email: suryoadhiwibowo@telkomuniversity.ac.id

1. INTRODUCTION

The fact about human death due to heart disease is no longer a secret. According to World Health Organization (WHO), heart disease results in 17.7 million human deaths in the world [1]. In this regard, research on electrocardiogram (ECG) signal analysis is very important. Research on ECG signal analysis is an important step in diagnosing heart disease. Research on the analysis of ECG signals has also been carried out for decades and the ECG signal itself has characteristics consisting of three main waves, namely the P wave, QRS complex and T wave. The QRS complex wave has useful information for the medical field such as RR interval, QT interval, and PR interval, so this QRS complex wave is an important wave for ECG signal based Health evaluation.

Initially, research on ECG signals or QRS wave detection focused on the pre-processing stage. At this stage usually use nonlinear or linear filters to reduce noise for example moving average filter [2], [3] wavelet transform [4]–[7], Hilbert transform [8], and squaring function [9]. Besides using filtering, some researchers use the adaptive threshold technique so that the proposed method can adapt to the shape of the ECG signal. For example, [10], using a combination of lowpass filter and irregular RR interval as a representation of a single level adaptive threshold. Meanwhile, for multi-level representation, [11] uses a combination of adaptive threshold.

In recent years, the development of deep learning is very rapid, especially in the medical field, for example its use for image analysis in radiology [12]. On the other hand, the ECG signal is a 1-dimensional (1D)

signal which if used deep learning for analysis is not suitable because the input for deep learning, especially the convolutional neural network (CNN) uses a 2-dimensional (2D) size. In this regard, the transformation from 1D to 2D is proposed so that the ECG signal input will conform to the CNN architecture. For example, spectrogram can be used to transform 1D data to the 2D data based on the short term Fourier transform (STFT). This approach was done by [13] using STFT and stationary wavelet transform (SWT), in his research, CNN is used to classify STFT and SWT outputs. The results of this study indicate that CNN outperforms compared to other methods. Although CNN has excellent results for the case of QRS complex detection, recurrent neural network (RNN) has advantages for time series data. On the other hand, the problem of gradients in the learning process is experienced by RNN. Gradient performance which does not have a significant effect on the learning process can be improved using the long short term memory (LSTM) method. Moreover, deep learning-based QRS complex detection and also the used of deep learning in ECG signal classification have been conducted in [14]–[26].

Considering these facts, in this paper we suggest a new method to improve the performance of QRS ECG signal detection by combining autoencoder and bidirectional long short term memory (BiLSTM). BiLSTM was chosen because the computational process is more efficient than using LSTM or RNN, long-term information loss, memory limitations and is prone to overfitting. Meanwhile, the autoencoder is used for the pre-processing and denoising of the ECG signal, which is more effective and provides better performance than using pre-processing techniques such as filtering. Furthermore, because of this fact, the combination between BiLSTM and stacked autoencoder is our contribution in this paper.

The remainder of this paper is organized as follows. Section 2 explains the concepts of the autoencoder, BiLSTM, ECG signal, and the proposed method. After that, experimental results with benchmark datasets and other advanced QRS complex detection methods are presented in section 3. Finally, conclusions and future work are presented in section 4.

2. METHOD

2.1. Autoencoder

Autoencoder is a method that uses an unsupervised learning approach. The autoencoder consists of three main parts, namely: encoder, decoder, and embedding. The function of the encoder in the autoencoder is to change the input data to match the conditions in the hidden representation. While the function of the decoder is a technique of reconstructing the input data from the hidden representation or layer. In this paper, we used stacked autoencoder and it has several hyperparameters that can affect the performance of a system. The hyperparameters are the number of layers, the number of nodes with embedding layers and a loss function. If we have input data $\{x\}_{p=1}^{(p)}$, where $x_p \in R^{m \times 1}$, h_p represents hidden encoder vector which calculated from x_p , and \hat{x}_p is the output from decoder called decoder vector. Further, the processes that perform in the encoder layer are:

$$h_p = f(W_1 x_p + b_1) \quad (1)$$

where W_1 , b_1 , and f are weight matrix of encoder, bias vector and a function from autoencoder itself, respectively.

Furthermore, the processes in the decoder are represented as (2) and (3):

$$\hat{x}_p = s(W_2 h_p + b_2), \quad (2)$$

$$A = \underset{\phi, \phi'}{\arg \min} \frac{1}{p} \sum_{i=1}^p L(x^i, \hat{x}^i) \quad (3)$$

where s , W_2 , b_2 , A , and L is a decoder function, weight matrix, bias parameter, optimization function, and loss function, respectively. Autoencoder architecture shown schematically Figure 1.

2.2. Bidirectional long short term memory

BiLSTM is a deep learning method that combines the bidirectional recurrent neural network algorithm with LSTM. LSTM arises from the problem of RNN where the more data is trained, the more gradients are removed. This makes the RNN lack the ability to understand information contextually. The thing that distinguishes RNN from LSTM is the process in one module. In RNN, one module only consist one activation

function single tanh layer that can be used for data classification, this fact is different compared to LSTM. In LSTM, consist four main components such as input gate, output gate, forget gate, and cell activation. Further, BiLSTM consist forward and backward LSTM where the forward pass represent as (4):

$$f_t = \alpha(W_f * [h_{t-1}, X_t] + b_f), \quad (4)$$

where α is sigmoid activation function, f_t represents the forget gate's output for time step t , W_f are the weights for the forget gate, h_{t-1} is the previous hidden state, X_t is the current input, b_f is the bias for the forget gate.

$$i_t = \alpha(W_i * [h_{t-1}, X_t] + b_i), \quad (5)$$

where i_t represents the input gate's output for time step t , W_i are the weights for the input gate, b_i is the bias for the input gate.

$$\hat{C}_t = \tanh(W_C * [h_{t-1}, X_t] + b_C) \quad (6)$$

where \hat{C}_t represents the candidate cell state for time step t , \tanh is the hyperbolic tangent activation function, W_C are the weights for the candidate cell state, b_C is the bias for the candidate cell state.

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t, \quad (7)$$

where C_t represents the update cell state for time step t , C_{t-1} is the previous update cell state.

$$o_t = \alpha(W_o * [h_{t-1}, X_t] + b_o), \quad (8)$$

where o_t represents the output gate's output for time step t , W_o are the weights for the output gate, b_o is the bias for the output gate. The equations for the backward pass are similar, but the sequence is processed in reverse order Figure 2 represents BiLSTM architecture.

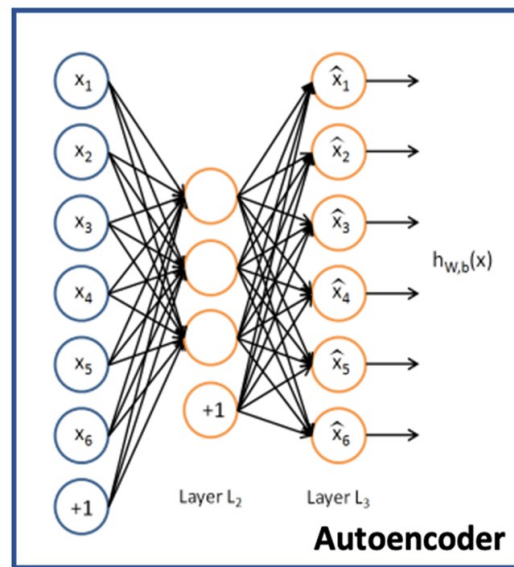


Figure 1. Stacked autoencoder architecture

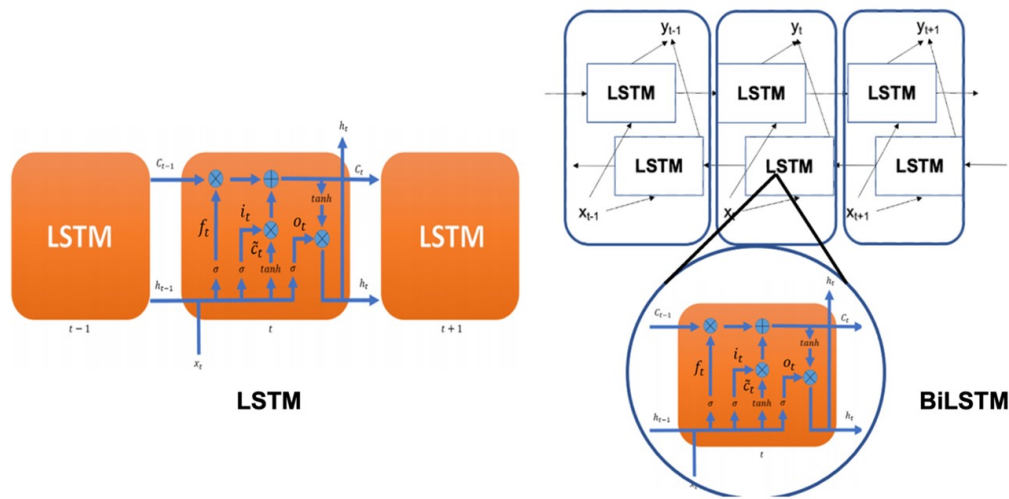


Figure 2. BiLSTM architecture

2.3. Electrocardiogram

ECG is a system that detects electrical signals caused by the activity of the heart muscles. The cycle of the heart rate on the ECG consists of P waves (P-wave), QRS complex, T-wave, and U-wave which is usually seen in almost 50%-70% of all ECGs. The base voltage of the ECG is known as the isoelectric line. Usually the isoelectric line is measured as part of the track that follows the T-wave and precedes the next P-wave. Figure 3 represent the waveform of ECG signal and its part.

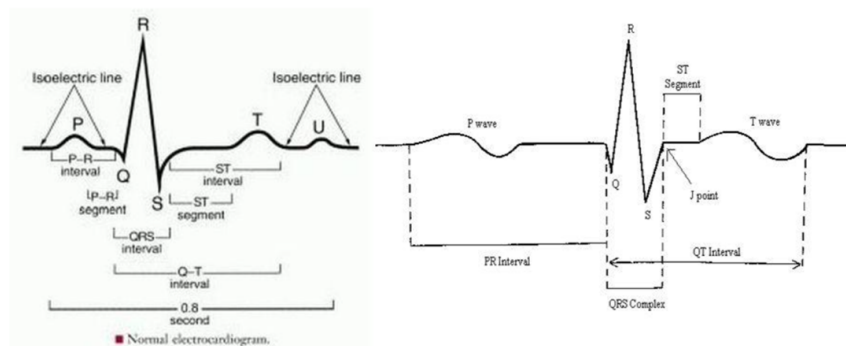


Figure 3. Waveform of ECG signal and its part

2.4. Proposed method

In this paper, MIT-BIH arrhythmia database is used to perform the experiment. In this dataset, ECG signal is extremely clean, so in order to represent the experiment in real condition, artificial noise is added by using MIT-BIH noise stress database with sampling frequency 250 Hz. In adding noise, we did as in previous research and also in TensorFlow guidance. The addition of noise represents the presence of noise in a device so that it affects the characteristics of the ECG signal. So that when this signal becomes an input to the proposed method, the signal reflects a real condition in an environment in the field. Further, according to this dataset, we divide it into 80% training data and 20% as a testing data. These data are completely independent from the other. Furthermore, the contribution in this paper is proposed BiLSTM to detect QRS complex signal and autoencoder is used to improve the detection performance. The specification of BiLSTM that used in this paper has 64 depth. In the other hand, exploration of autoencoder also performed in this paper. The stacked autoencoder is used in this paper and investigate the depth specification are: 128-64, 128-32, 128-16, 128-

8, 128-4, 64-32, 64-16, 64-8, 64-4, 32-16, 32-8, 32-4, 16-8, 16-4, and 8-4. The rule to implement stacked autoencoder is the depth size of encoder should larger than decoder. Furthermore, experimental is done in GPU 1×Tesla K80, 12 GB GDDR5 VRAM, and 1×single core hyper threaded Xeon processors @2.3 Ghz.

Moreover, the representation of our proposed method is described in Figure 4. In this method, there are two main parts: stacked autoencoder and BiLSTM. The input of the system is ECG signal from MIT-BIH arrhythmia database that has been added artificial noise. Because the input ECG signal is noisy, filtering by using stacked autoencoder is performed. Stacked autoencoder is used because it has advantages to perform filtering. The stacked autoencoder may reduce the dimensionality of the data and it can reach global optima for the optimization. Figure 5 represent the baseline wander and muscle artifact for ECG signal. Figures 6 and 7 represent the normal beats and premature ventricular contractions also the training data and its label, respectively. The output from stacked autoencoder is computed in BiLSTM by using number of batch 256 and steps 1000. These numbers are directly chose, the number of batches used to be 256, this is a representation of 2^n , and the number 256 is considered sufficient for this process, including the number of steps of 1000 which is considered neither too little nor too big. The choice of the number of batches and steps in this research are needed to be explored for the future research because the focus of this research is the exploration of depth in stacked autoencoders and the use of BiLSTM. This BiLSTM has advantages to process the sequential data.

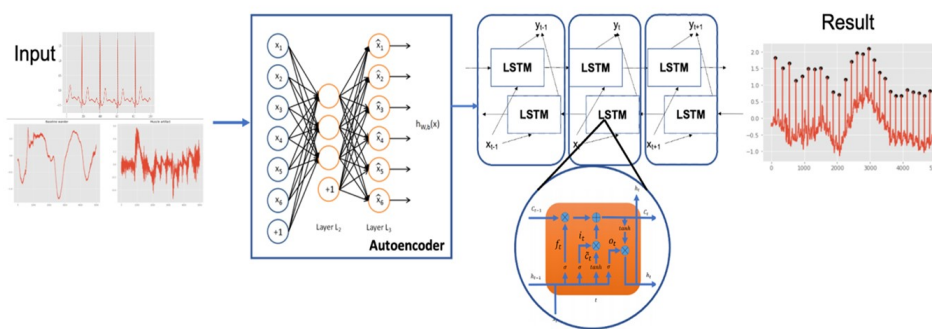


Figure 4. Proposed method

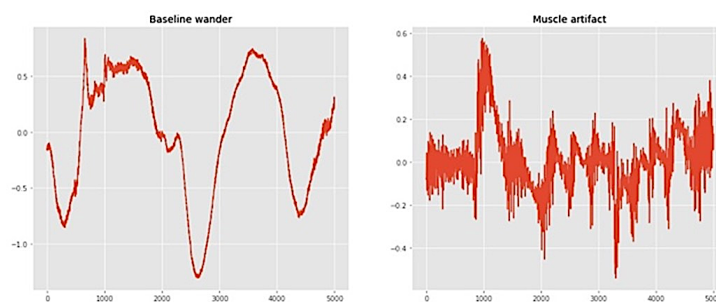


Figure 5. Representation of baseline wander and muscle artifact

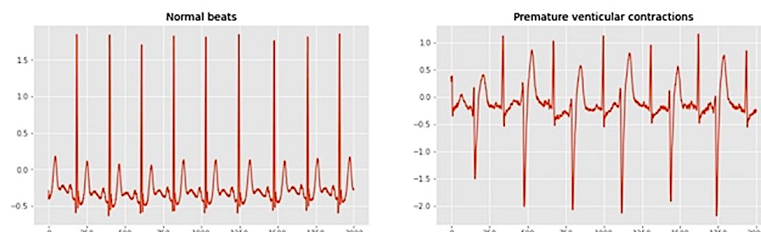


Figure 6. Representation of normal beats and premature ventricular contractions

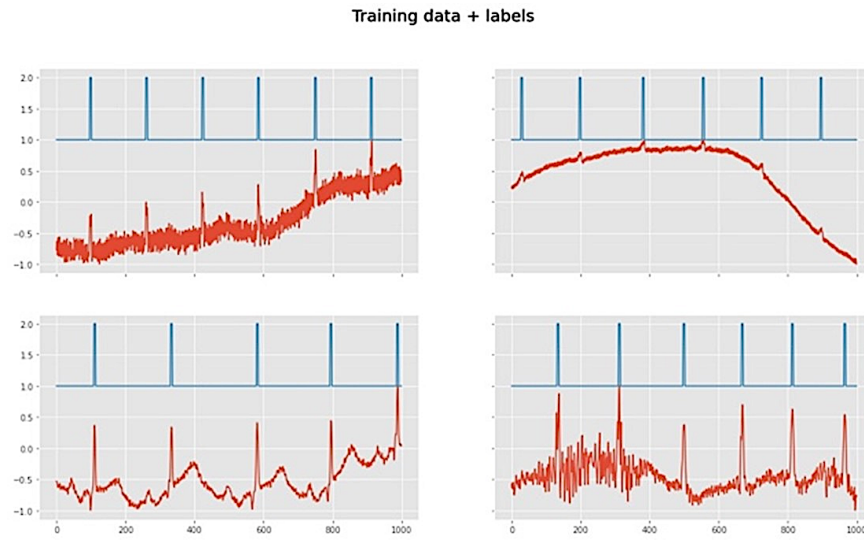


Figure 7. Representation of training data and its label

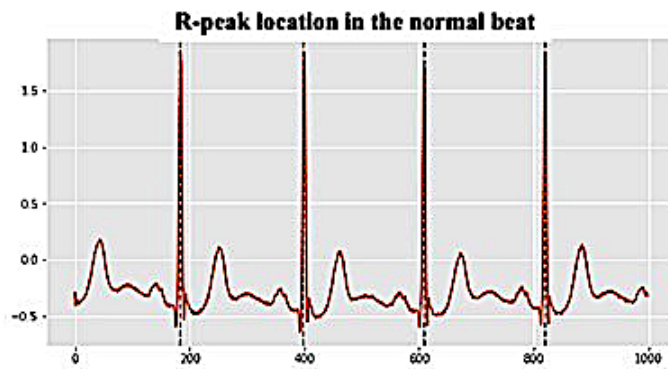


Figure 8. Representation of R-peak location in the normal beats

2.5. Performance metrics

In order to calculate the performance of the proposed method, the performance metrics are used as (9)–(12):

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (9)$$

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (12)$$

where TP , TN , FP , and FN are true positive, true negative, false positive, false negative, respectively.

3. RESULT AND DISCUSSION

In this research, the exploration of hyperparameter (Depth) in stacked autoencoder is performed. The exploration parameter that used in this research explained in this section. Furthermore, we used the number of

epoch is 50 epoch because in this research, we concern to the investigating the impact of stacked autoencoder when implementing to BiLSTM and also exploring the hyperparameter that suitable for QRS complex detection case.

The results of this research is represented in Tables 1 and 2. In the Table 1, the results from hyperparameter (Depth) exploration of stacked autoencoder are served. In this table, we can see when the depth of stacked autoencoder is deeper, small epoch cannot perform well. The example of this case can be seen for the hyperparameters 128-32, 128-16, 64-16, 64-8, and 64-4. In these depths, the parameter performances such as F1-score, precision, and recall cannot be generated because the training process cannot reach the convergence condition. This is similar with the hyperparameter 64×32 , even though the parameter performances can be calculated, the results are extremely low. Furthermore, the hyperparameter 16-8 of stacked autoencoder performed excellence with the accuracy training and testing are 99.89% and 99.94%, respectively. This condition is out performed compared the proposed method (NSA: BiLSTM without stacked autoencoder), where the result only achieve 99.61 for training accuracy and 99.54% for testing accuracy. The hyperparameter 16-8 also give best result for other performance parameters (F1-score, precision, and recall) compared to the NSA and BiLSTM using stacked autoencoder with other hyperparameter configuration. It is because the optimal hyperparameter configuration for QRS complex detection case is 16-8, where this depth size is not much deeper.

In the Table 2, the best hyperparameter configuration result from Table 1 is selected and compared to the other state of the art method QRS complex detection. We compared our proposed method with Pan and Tompkins method [27], Chen and Chuang method [28], and Lu *et al.* [29]. Method that using adaptive threshold for detect the QRS complex signal.

Table 1. Autoencoder performance evaluation (training/testing) with epoch 50

| Proposed | Autoencoder performance evaluation (training and testing) | | | | | | | |
|----------|-----------------------------------------------------------|-------|-----------|-------|--------|-------|----------|-------|
| | F1-score | | Precision | | Recall | | Accuracy | |
| 128-64 | 89.87 | 89.87 | 91.45 | 93.02 | 88.36 | 86.94 | 99.51 | 99.47 |
| 128-32 | 0 | 0 | 0 | 0 | 0 | 0 | 99.53 | 97.40 |
| 128-16 | 0 | 0 | 0 | 0 | 0 | 0 | 99.53 | 97.40 |
| 128-8 | 90.03 | 90.69 | 91.75 | 92.12 | 88.42 | 88.16 | 99.52 | 99.50 |
| 128-4 | 89.20 | 90.68 | 90.67 | 92.32 | 87.79 | 89.09 | 99.47 | 99.52 |
| 64-32 | 13.48 | 64.13 | 18.56 | 79.80 | 11.56 | 53.65 | 97.71 | 98.44 |
| 64-16 | 0 | 0 | 0 | 0 | 0 | 0 | 97.52 | 97.40 |
| 64-8 | 0 | 0 | 0 | 0 | 0 | 0 | 97.52 | 97.39 |
| 64-4 | 0 | 0 | 0 | 0 | 0 | 0 | 97.52 | 97.39 |
| 32-16 | 91.06 | 91.24 | 92.31 | 93.74 | 89.84 | 88.88 | 99.56 | 99.56 |
| 32-8 | 90.39 | 90.87 | 91.81 | 92.24 | 89.02 | 89.54 | 99.53 | 99.53 |
| 32-4 | 91.30 | 90.61 | 92.17 | 92.69 | 90.47 | 88.62 | 99.58 | 99.52 |
| 16-8 | 92.22 | 91.02 | 92.95 | 93.23 | 91.50 | 88.91 | 99.89 | 99.94 |
| 16-4 | 91.61 | 90.57 | 92.33 | 92.56 | 90.91 | 88.66 | 99.59 | 99.52 |
| 8-4 | 90.56 | 90.09 | 91.61 | 91.56 | 89.55 | 88.68 | 99.54 | 99.49 |
| NSA | 91.97 | 91.00 | 92.73 | 92.69 | 91.22 | 89.37 | 99.61 | 99.54 |

Table 2. Performance comparison using other state-of-the-art method

| Method | Accuracy |
|-----------------------|--------------|
| Pan and Tompkins [27] | 99.29 |
| Chen and Chuang [28] | 99.02 |
| Lu <i>et al.</i> [29] | 99.54 |
| Proposed (NSA) | 99.54 |
| Proposed (16-8) | 99.94 |

Based on the result comparison in the Table 2, our proposed method (using stacked autoencoder and without stacked autoencoder) are outperformed to the other state of the art method. Our proposed method (using stacked autoencoder 16-8) achieved the accuracy parameter 0.54 better than Lu *et al.* [29]. Method that using adaptive threshold and it is proved that BiLSTM performed very well to handle sequence data and also by adding stacked autoencoder in the pre-processing step may improve the performance the original BiLSTM.

In this paper, BiLSTM is implemented for detecting QRS complex signal and by adding the stacked autoencoder, the performance is improve. The exploration of hyperparameter in stacked autoencoder is a one of focus of this paper. Based on the result, we may achieve high performance by using only small epoch. Because

of this fact, our proposed method can save the computation resources. Future research for this topic also still have opportunity such as the implementation to the low cost computational hardware and real time processing.

4. CONCLUSION

In this paper, QRS complex detection method based on BiLSTM and improved by using stacked autoencoder are proposed and validated with the MIT-BIH arrhythmia database. Moreover, the hyperparameter exploration of the stacked autoencoder (Depth) is done. The performance of the proposed method gives the accuracy of 99.54% and improved 0.4 when implemented BiLSTM with stacked autoencoder. This performance also higher 0.54 than the other state of the art QRS complex detection method. By using only small epoch, our proposed method may achieved very well result and proves that our proposed method can save computational resources.

ACKNOWLEDGEMENT

The author would like to thank to the Ministry of Finance Republic of Indonesia, Indonesia Endowment Fund for Education Agency (LPDP) and National Research and Innovation Agency (BRIN) under RIIM batch 4 program (reg. number: RIIM-331664610056) and also BRIN talent management for providing the Degree By Research (DBR) program scholarship so that this research can be carried out.




REFERENCES

- [1] W. H. Organization, "Cardiovascular diseases (cvds)". [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-cvds>. (accessed: Jun. 11, 2021).
- [2] Z.-E. H. Slimane and A. Nait-Ali, "QRS complex detection using empirical mode decomposition," *Digital signal processing*, vol. 20, no. 4, pp. 1221–1228, Jul. 2010, doi: 10.1016/j.dsp.2009.10.017.
- [3] S. Chouakri, F. Bereksi-Reguig, and A. Taleb-Ahmed, "QRS complex detection based on multi wavelet packet decomposition," *Applied Mathematics and Computation*, vol. 217, no. 23, pp. 9508–9525, 2011, doi: 10.1016/j.amc.2011.03.001.
- [4] M. S. Manikandan and K. Soman, "A novel method for detecting r-peaks in electrocardiogram (ECG) signal," *Biomedical Signal Processing and Control*, vol. 7, no. 2, pp. 118–128, Mar. 2012, doi: 10.1016/j.bspc.2011.03.004.
- [5] H. Zhu and J. Dong, "An R-peak detection method based on peaks of shannon energy envelope," *Biomedical Signal Processing and Control*, vol. 8, no. 5, pp. 466–474, 2013, doi: 10.1016/j.bspc.2013.01.001.
- [6] F. Bouaziz, D. Boutana, and M. Benidir, "Multiresolution wavelet- based QRS complex detection algorithm suited to several abnormal morphologies," *IET Signal Processing*, vol. 8, no. 7, pp. 774–782, Sep. 2014, doi: 10.1049/iet-spr.2013.0391.
- [7] A. Karimipour and M. R. Homaeinezhad, "Real-time electrocardiogram p-qrs-t detection–delineation algorithm based on quality-supported analysis of characteristic templates," *Computers in biology and medicine*, vol. 52, pp. 153–165, Sep. 2014, doi: 10.1016/j.compbiomed.2014.07.002.
- [8] J. P. Madeiro, P. C. Cortez, J. A. Marques, C. R. Seisdedos, and C. R. M. R. Sobrinho, "An innovative approach of QRS segmentation based on first- derivative, hilbert and wavelet transforms," *Medical engineering & physics*, vol. 34, no. 9, pp. 1236–1246, 2012, doi: 10.1016/j.medengphy.2011.12.011.
- [9] M. Adnane, Z. Jiang, and S. Choi, "Development of QRS detection algorithm designed for wearable cardiorespiratory system," *Computer Methods and Programs in Biomedicine*, vol. 93, no. 1, pp. 20–31, 2009, doi: 10.1016/j.cmpb.2008.07.010.
- [10] S. Choi, M. Adnane, G.-J. Lee, H. Jang, Z. Jiang, and H.-K. Park, "Development of ECG beat segmentation method by combining lowpass filter and irregular r–r interval checkup strategy," *Expert Systems with Applications*, vol. 37, no. 7, pp. 5208–5218, 2010, doi: 10.1016/j.eswa.2009.12.069.
- [11] I. I. Christov, "Real time electrocardiogram QRS detection using combined adaptive threshold," *BioMedical Engineering OnLine*, vol. 3, no. 1, p. 28, 2004, doi: 10.1186/1475-925X-3-28.
- [12] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," *Insights into imaging*, vol. 9, pp. 611–629, 2018, doi: 10.1007/s13244-018-0639-9.
- [13] Y. Xia, N. Wulan, K. Wang, and H. Zhang, "Atrial fibrillation detection using stationary wavelet transform and deep learning," *2017 Computing in Cardiology (CinC)*, Rennes, France, 2017, pp. 1–4, doi: 10.22489/CinC.2017.210-084.
- [14] M. Ramkumara, R. S. Kumarb, A. Manjunathanc, M. Mathankumard, and J. Pauliah, "Auto-encoder and bidirectional long short-term memory based automated arrhythmia classification for ECG signal," *Biomedical Signal Processing and Control*, vol. 77, p. 103826, Aug. 2022, doi: 10.1016/j.bspc.2022.103826.
- [15] S. Kusuma and J. K. R., "ECG signals-based automated diagnosis of congestive heart failure using Deep CNN and LSTM architecture," *Biocybernetics and Biomedical Engineering*, vol. 42, no. 1, 247–257, 2022, doi: 10.1016/j.bbe.2022.02.003.
- [16] H. Li et al., "Automatic electrocardiogram detection and classification using bidirectional long short-term memory network improved by Bayesian optimization," *Biomedical Signal Processing and Control*, vol. 73, p. 103424, 2022, doi: 10.1016/j.bspc.2021.103424.
- [17] P. Varalakshmi and A. P. Sankaran, "An improved hybrid AI model for prediction of arrhythmia using ECG signals," *Biomedical Signal Processing and Control*, vol. 80, p. 104248, Feb. 2023, doi: 10.1016/j.bspc.2022.104248.
- [18] A. E. Curtin, K. V. Burns, A. J. Bank, and T. I. Netoff, "QRS Complex Detection and Measurement Algorithms for Multichannel ECGs in Cardiac Resynchronization Therapy Patients," in *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 6, pp. 1–11, 2018, doi: 10.1109/JTEHM.2018.2844195.




- [19] X. Tang, Q. Hu, and W. Tang, "A Real-Time QRS Detection System With PR/RT Interval and ST Segment Measurements for Wearable ECG Sensors Using Parallel Delta Modulators," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 12, no. 4, pp. 751-761, Aug. 2018, doi: 10.1109/TBCAS.2018.2823275.
- [20] J. Shweta, A. Kumar, and V. Bajaj, "Technique for QRS complex detection using particle swarm optimization," *IET Science, Measurement & Technology*, vol. 10, no. 6, pp. 626-636, Sep. 2016, doi: 10.1049/iet-smt.2016.0023.
- [21] H. V. Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double q-learning," *Thirtieth AAAI conference on artificial intelligence*, vol. 30, no. 1, Mar. 2016, doi: 10.1609/aaai.v30i1.10295.
- [22] R. Mark, R. Dadashi, S. Kumar, R. Munos, M. G. Bellemare, and W. Dabney, "Statistics and samples in distributional reinforcement learning," *Proceedings of the 36th International Conference on Machine Learning*, May 2019, pp. 5528-5536.
- [23] M. G. Bellemare, W. Dabney, and R. Munos, "A distributional perspective on reinforcement learning," *International conference on machine learning*, Jul. 2017, pp. 449-458.
- [24] M. Kashif, S. M. Jonas, and T. M. Deserno, "Deterioration of R-Wave Detection in Pathology and Noise: A Comprehensive Analysis Using Simultaneous Truth and Performance Level Estimation," in *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 9, pp. 2163-2175, Sep. 2017, doi: 10.1109/TBME.2016.2633277.
- [25] L. Seungmin, D. Park, and K. Park, "QRS complex detection based on primitive," in *Journal of Communications and Networks*, vol. 19, no. 5, pp. 442-450, Oct. 2017, doi: 10.1109/JCN.2017.000076.
- [26] H. Khamis, R. Weiss, Y. Xie, C. -W. Chang, N. H. Lovell, and S. J. Redmond, "QRS Detection Algorithm for Telehealth Electrocardiogram Recordings," in *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 7, pp. 1377-1388, Jul. 2016, doi: 10.1109/TBME.2016.2549060.
- [27] J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," in *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230-236, Mar. 1985, doi: 10.1109/TBME.1985.325532.
- [28] C.-L. Chen and C.-T. Chuang, "A QRS detection and r point recognition method for wearable single-lead ecg devices," *Sensors*, vol. 17, no. 9, 2017, doi: 10.3390/s17091969.
- [29] X. Lu, M. Pan, and Y. Yu, "QRS detection based on improved adaptive threshold," *Journal of healthcare engineering*, vol. 2018, pp. 1-8, 2018, doi:10.1155/2018/5694595.

BIOGRAPHIES OF AUTHORS



Asep Insani    obtained his Bachelor's degree from the Telkom College of Technology in 2004. M.Sc. degree in Computer Science from Universitas Indonesia in 2011 Ph.D. student in 2019 until 2021. He works as a researcher at the National Research and Innovation Agency. His research is related to instrumentation, artificial intelligence, and radiation thermometer. He has produced more than 30 national and international publications. He can be contacted at email: asepo35@brin.go.id.



Suryo Adhi Wibowo    received B.Sc. and M.Sc. majoring Telecommunication Engineering from Telkom University (previously known as Telkom Institute Of Technology), Indonesia, in 2009 and 2012, respectively. He received Ph.D degree from the Department of Electrical and Computer Engineering, Pusan National University, Republic of Korea in 2018. He has been an Assistant Professor of Telecommunication Engineering with Telkom University since 2010 and He is currently the Vice Director of The Artificial Intelligence Center (AI Center) Telkom University. He is a member of IEEE and also member of Indonesia Artificial Intelligence Research Consortium (IARC). He can be contacted at email: suryoadhiwibowo@telkomuniversity.ac.id.